SALES PREDICTION USING PYTHON

CODSOFT

Step 1: Import Libraries

First, import the necessary libraries for data manipulation, visualization, and modeling.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Step 2: Load the Data

Load your dataset into a Pandas DataFrame:

```
data = pd.read_csv("C:\\Users\\Narthana\\Downloads\\advertising.csv")
```

Step 3: Data Cleaning

Check for missing values and handle them if necessary. In this dataset, there might not be any missing values, but it's good practice to check.

```
data.isnull().sum()
```

```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

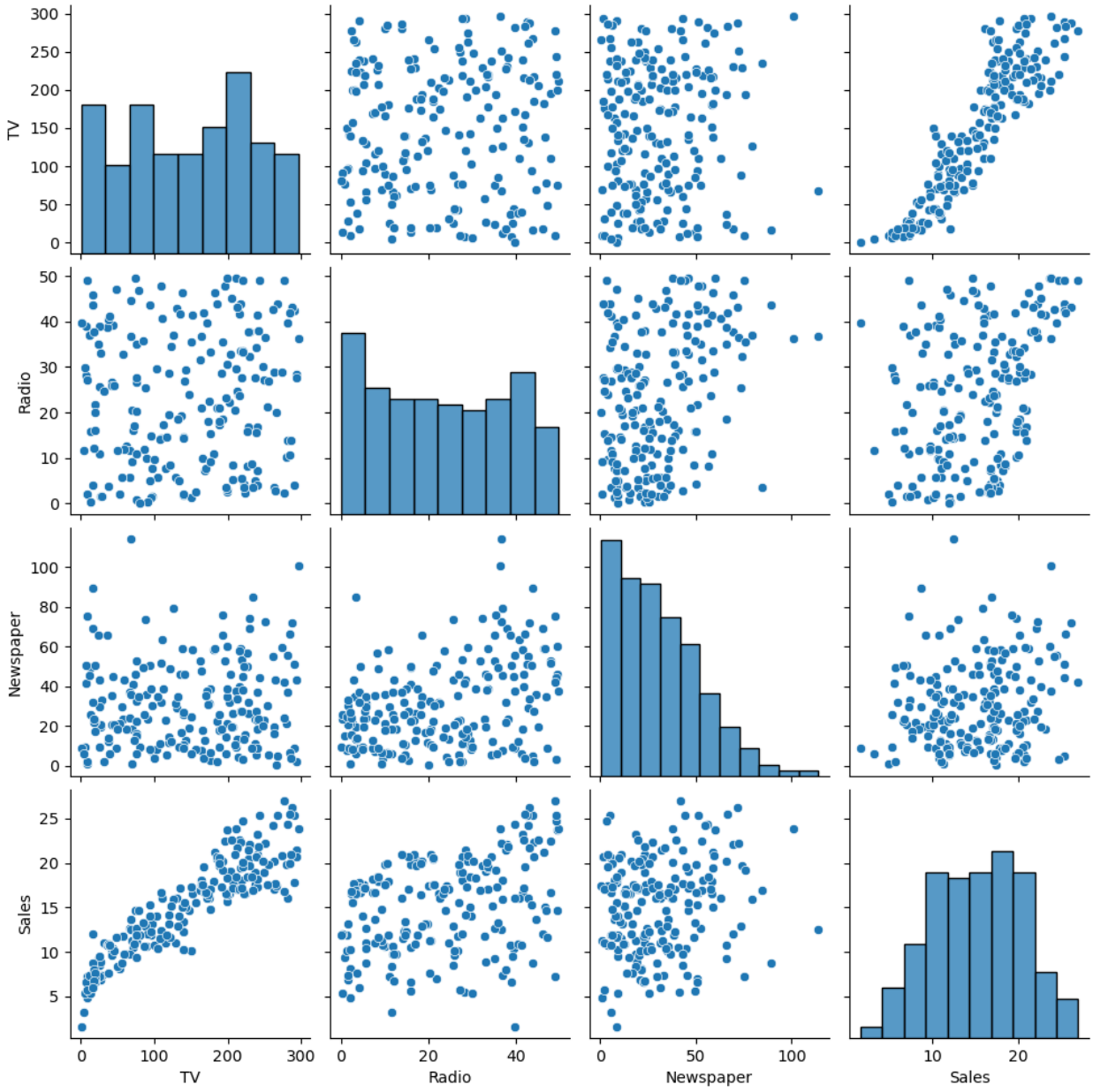
Step 4: Exploratory Data Analysis (EDA)

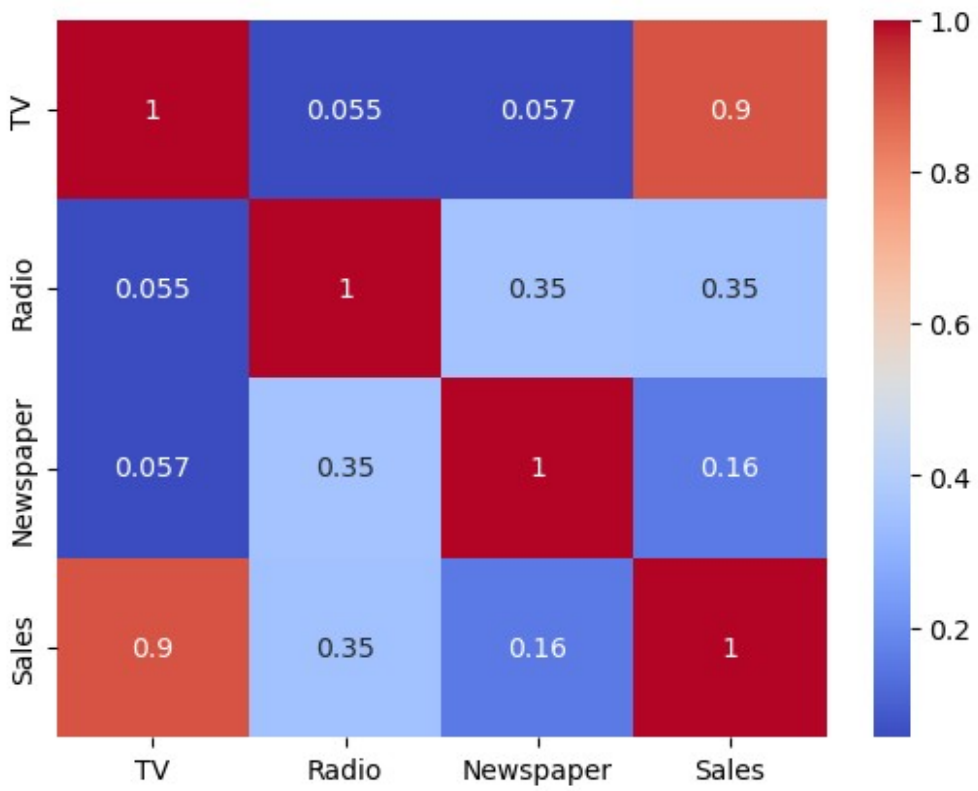
Perform EDA to understand the data's distribution, relationships, and statistics. Use various visualizations to gain insights:

```
# Summary statistics
print(data.describe())

# Pairplot for visualizing relationships between variables
```

```
sns.pairplot(data)
plt.show()

# Correlation heatmap
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000


TV
Radio
Newspaper
Sales
0
50
100
150
200
250
300
0
10
20
30
40
50
0
20
40
60
80
100
5
10
15
20
25
0
100
200
300
0
20
40
0
50
100
10
20



Calculating Average Sales:

To calculate the average sales from your dataset, you can simply use the mean() function on the 'Sales' column:

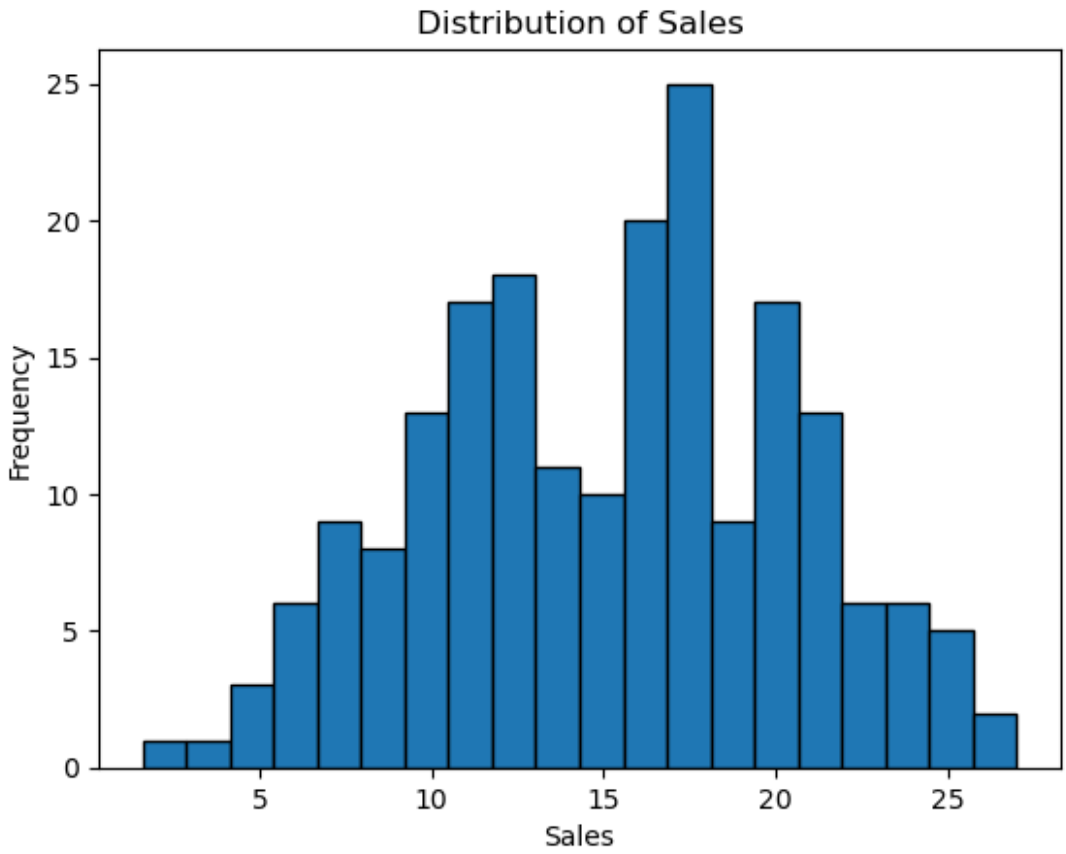
```
average_sales = data['Sales'].mean()
print("Average Sales:", average_sales)
```

```
Average Sales: 15.130500000000001
```

Histogram of Sales:

Visualize the distribution of sales values using a histogram.

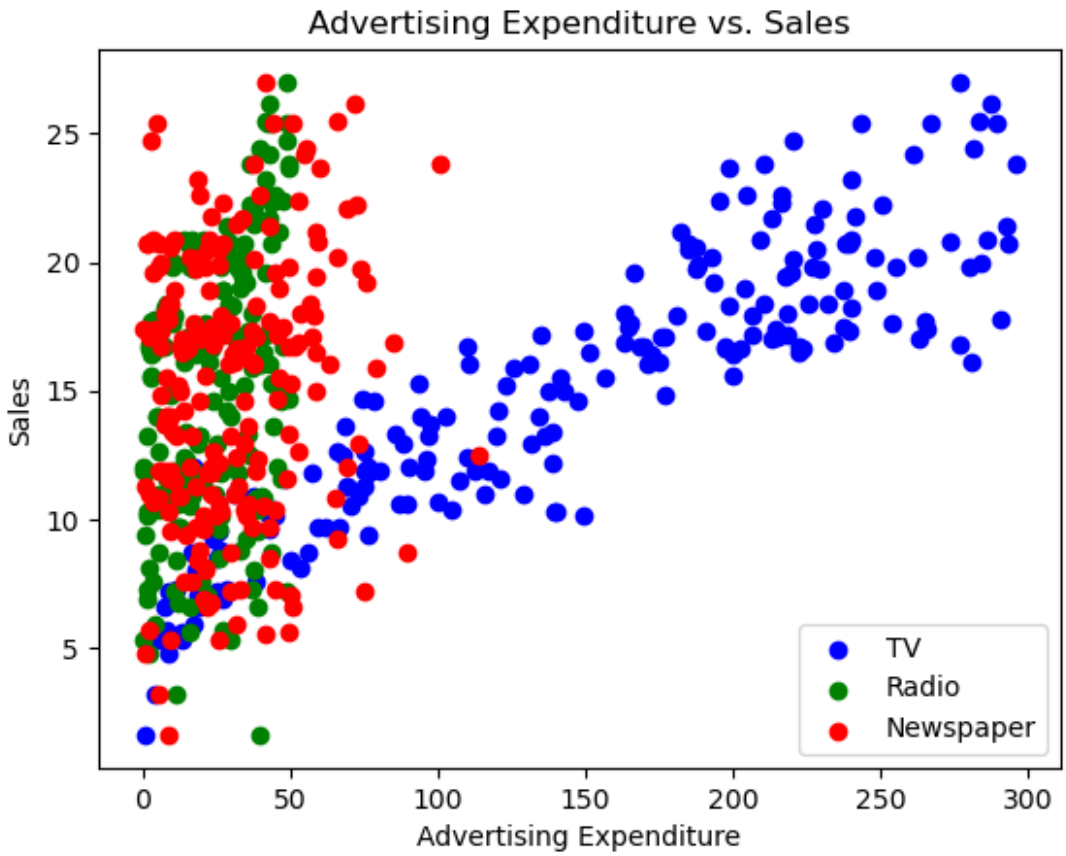
```
plt.hist(data['Sales'], bins=20, edgecolor='k')
plt.xlabel('Sales')
plt.ylabel('Frequency')
plt.title('Distribution of Sales')
plt.show()
```



Scatter Plots for Individual Advertising Channels:

Create scatter plots to see the relationship between each advertising channel (TV, Radio, Newspaper) and sales.

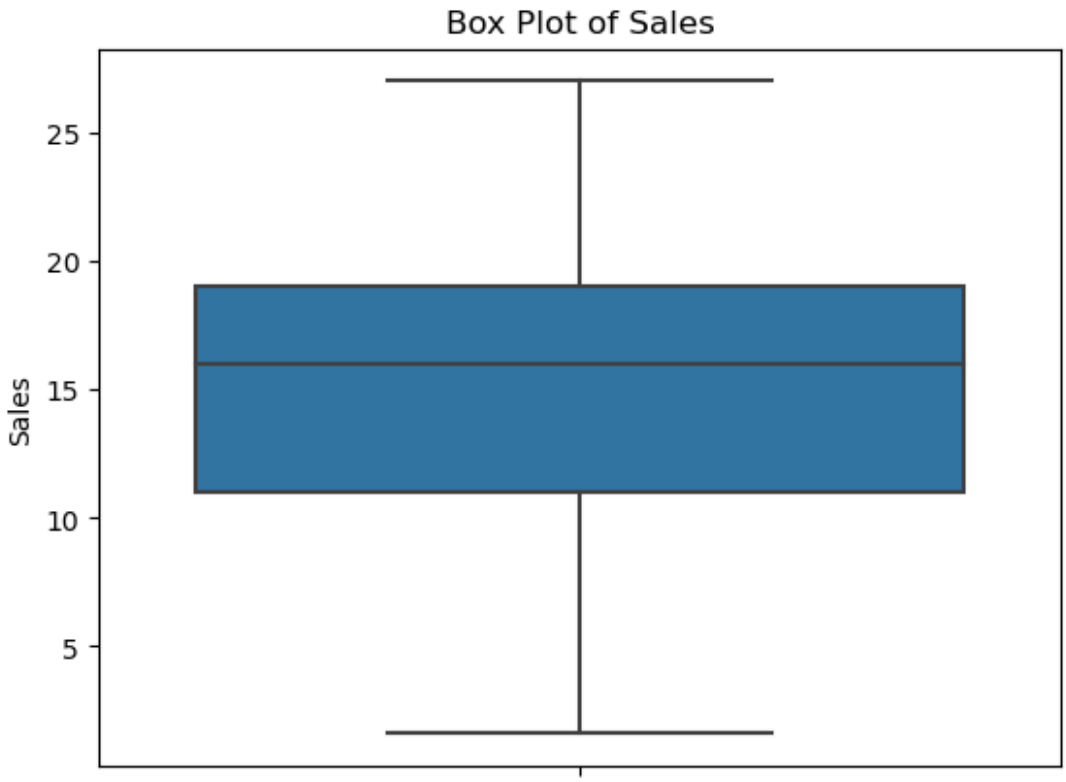
```
plt.scatter(data['TV'], data['Sales'], c='blue', label='TV')
plt.scatter(data['Radio'], data['Sales'], c='green', label='Radio')
plt.scatter(data['Newspaper'], data['Sales'], c='red',
label='Newspaper')
plt.xlabel('Advertising Expenditure')
plt.ylabel('Sales')
plt.legend()
plt.title('Advertising Expenditure vs. Sales')
plt.show()
```



Box Plot for Sales:

Create a box plot to visualize the distribution of sales and identify potential outliers.

```
sns.boxplot(y=data['Sales'])
plt.ylabel('Sales')
plt.title('Box Plot of Sales')
plt.show()
```



Descriptive Statistics: You calculate and print summary statistics for the 'Sales' column, including measures like mean, standard deviation, minimum, maximum, and quartiles.

Outlier Detection: You use the interquartile range (IQR) method to detect potential outliers. Any data points falling below Q1 - 1.5 * IQR or above Q3 + 1.5 * IQR are considered potential outliers. These outliers are printed at the end.

```
# Descriptive statistics
summary_stats = data['Sales'].describe()

# Detect and print potential outliers
Q1 = data['Sales'].quantile(0.25)
Q3 = data['Sales'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
outliers = data[(data['Sales'] < lower_bound) | (data['Sales'] >
upper_bound)]

print("Summary Statistics for Sales:")
print(summary_stats)
print("\nPotential Outliers:")
print(outliers)
```

```
Summary Statistics for Sales:
count    200.000000
```

```
mean      15.130500
std        5.283892
min        1.600000
25%       11.000000
50%       16.000000
75%       19.050000
max       27.000000
Name: Sales, dtype: float64

Potential Outliers:
Empty DataFrame
Columns: [TV, Radio, Newspaper, Sales]
Index: []
```

Step 5: Feature Selection

Based on the EDA, select the relevant features (independent variables) for the prediction. In this case, it appears that TV, Radio, and Newspaper advertising expenditures are relevant for predicting sales.

```
X = data[['TV', 'Radio', 'Newspaper']]
y = data['Sales']
```

Step 6: Split Data into Training and Testing Sets

Split the data into training and testing sets to train and evaluate the model.

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Step 7: Model Training

Train a linear regression model on the training data:

```
model = LinearRegression()
model.fit(X_train, y_train)

LinearRegression()
```

Step 8: Model Evaluation

Evaluate the model's performance on the test data:

```
y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
print("Mean Squared Error:", mse)
print("R-squared:", r2)
```

```
Mean Squared Error: 2.907756910271089
R-squared: 0.9059011844150826
```

Step 9: Make Predictions

```
new_data = pd.DataFrame({'TV': [200], 'Radio': [40], 'Newspaper':
[20]})
predicted_sales = model.predict(new_data)
print("Predicted Sales:", predicted_sales[0])
```

```
Predicted Sales: 19.740528001816998
```

Step 10: Inference

Based on the output and visualizations, you can draw the following inferences:

TV advertising expenditure has a strong positive correlation with sales. Radio advertising expenditure also has a positive correlation with sales but weaker than TV. Newspaper advertising expenditure has a relatively weak positive correlation with sales.